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The geography of hospital admission in a National Health Service with patient choice: evidence from Italy

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Abstract: It is evaluated that, each year, 35% out of the 10 million hospital admissions in Italy take place outside the LHAs of residence. In our paper we try to give an explanation of this phenomenon making reference to the social gravity model of spatial interaction. We estimate gravity equations using a Poisson pseudo maximum likelihood method, as proposed by Santos-Silva and Tenreyro (2006). Our results suggest that the gravity model is a good framework for explaining the patient mobility phenomenon for most of the examined diagnostic groups. Our evidence suggests that the ability to contain the imports of hospital services increases with the size of the pool of enrolees. Moreover we find that the ability to export hospital services, as proxied by the ratio of export-to-internal demand, is U-shaped. Therefore our evidence suggests that there are scale effect played by the size of the pool of enrolees.

Keywords: patients' mobility, hospital care, gravity model, Italian National Health Service

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1 INTRODUCTION

Each year, it is estimated that 35% out of the 10 million hospital admissions in Italy takes place outside the patients' Local Health Authority of residence. This figure goes up to almost 42% for cancer treatment and more than 58% for complex surgery. This situation raises policy concerns due to the peculiar institutional setting that drives the allocation of resources in this sector.

In the Italian NHS patients are enrolled into health plans managed by Local Health Authorities (LHAs). Enrolment is based on a patient's place of residence, while funds to enrolling LHAs accrues from general taxation according to a capitation payment per enrolee. With the available resources LHAs are responsible for the healthcare consumption of their enrolees. Concerning hospital care, patients are entitled to completely free of charge treatments, providers being ex-post reimbursed by patient's LHAs according to centrally set prices. A distinctive feature of the Italian NHS is that within this institutional framework (similar to many other "decentralized" tax-funded NHS systems, like for example, Spain, Norway, Denmark, and the UK) patients can freely choose the provider of hospital care.

Equity of access and financial sustainability are the main concerns arising from this situation. Exit rates and average distance travelled to access hospital care are, for instance, much larger for enrolees in southern LHAs. Observed imbalances in patient mobility make the distribution of private mobility costs uneven and promote the accumulation of financial resources towards the already better endowed LHAs. In this paper we aim to evaluate the extent to which the observed imbalances in the Italian geography of hospital admission are due to scale effects, depend on a core/periphery equilibrium, or reflect a deeper, long lasting north/south divide. In particular, we focus on the scale effect played by the size of the pool of enrolees. 25% of Italian LHAs have less than 150,000 enrolees, while 20% have more than 400,000 enrolees. Since funds accrue to LHAs on a capitation basis, and smaller LHAs suffer from relatively larger patients' outflows while receiving smaller inflows, this policy variable is crucial in determining LHAs financial stability.

We work on an origin/destination matrix provided by the Italian Ministry of Health, comprising all ordinary admissions to public hospitals in Italy during the year 2001. We classify hospital admissions into 4 broad diagnostic groups. To control for distance, contiguity, and supply characteristics, we estimate a gravity equation for the full matrix of pair-wise flows. We estimate gravity equations in multiplicative form adopting a Poisson pseudo maximum likelihood approach, as proposed by Santos-Silva and Tenreyro (2006). This method is robust to different patterns of heteroskedasticity and provides a natural way to deal with the zero flows.

Our results suggest that the gravity model proves to be a good framework for explaining the patient mobility phenomenon for most of the examined diagnostic groups. We find evidence for the ability to contain imports of hospital services is increasing in the size of the pool of enrolees. Moreover the ability to export hospital services, as proxied by the ratio of export-to-internal demand, appear to follow a U-shaped curve.

The paper is organized as follows. The next section provides concise institutional background on the market for hospital care in Italy. Section 3 presents our base of data and some preliminary evidence. Section 4 contains a literature review on gravity models. Section 5 details our econometric model and estimation strategy. Section 6 describes the data and the empirical specification of our model. Major results are presented in section 7. Section 8 concludes.

2 INSTITUTIONAL BACKGROUND AND MOTIVATION

Patient mobility causes concern, particularly in relation to the reforms that occurred in the Italian health care sector in the late ’90s. The National Health Service (otherwise known as SSN - Servizio Sanitario Nazionale) was created in 1978 as a regionally based system providing universal coverage free of charge at the point of service. The central government was responsible for determining the amount of resources to devote to health care, for general planning, and for funding Regions through general taxation and compulsory health contributions.[1] The 20 Regional authorities were responsible for local planning according to the objectives specified by the central government, and for allocating resources to the third level of the system, the Local Health Units. These were operational agencies in charge of providing services to patients through their own facilities or through contracts with private providers. They provide a wide range of services, at hospital and community level, in geographical areas with populations of about 300,000. The LHAs do not have revenues collection responsibilities, but they are funded by the Regions through a capitation system (France et al., 2005)

The Italian National Health System is quite fragmented in terms of organization of the regional services. At one end of the spectrum there is the “LHA-centred model”, where the LHAs have substantial freedom in negotiating service agreements with public and accredited private providers. At the other end of the spectrum there is the “Region-centred model”, where the regions exercise a purchaser role and fund the providers directly, while the LHAs have little organizational freedom and act mainly as providers (France et al., 2005)

[1] Depending on a citizen's income, age and health condition, co-payments are also charged for drugs, out-patient treatment, some diagnostic and laboratory tests, and medical appliances.

The SSN guaranteed the provision of hospital treatments at a given level of quality and free of charge. On the supply side, the SSN largely relies on public production supplemented by privately licensed hospitals. Public hospitals are run by LHAs or by autonomous public trusts (Aziende Ospedaliere, Policlinici and Istituti di Ricovero e cura a carattere scientifico (IRCCS)). Privately licensed hospitals can treat patients within the SSN, i.e. free of charge, and are refunded afterwards by the LHA to which the patient is enrolled. Patients are completely free to choose their hospital; it may be publicly or privately licensed, and within or outside the LHA where they are enrolled.

The functioning of such a decentralized public health care service has recently been reformed through the approval of Legislative Decrees 502/1992 and 517/1993 with the purported aim of introducing some elements of internal market competition. Significant managerial autonomy has been devolved to larger hospitals and LHAs, and, at the same time, a partial split between health care production and purchasing has been introduced. Competition has been promoted by the introduction of prospective payment for hospital admission through the Diagnosis Related Groups (DRGs) classification scheme. Since the year 2000, public hospital treatments have been priced through the DRG scheme according to fixed prices set at national level. Regions sets their tariffs referring to national tariffs rates, which represents a ceiling and allow flexibility downward (so far they have been reduced by up to – 30% of national tariffs) (France et al. 2005). The Legislative Decrees have also introduced some elements of regional federalism, which were strengthened by Legislative Decree 446/1997 (introducing sources of autonomous financing for the regions) and Decree 56/2000 (stating that the funding of the NHS is mainly the responsibility of the Regions).[2] [3] Regions can choose how many resources to spend in the health care sector, subject to some constraints. They have to guarantee a minimum level of health care (*livelli essenziali di assistnza* – LEAs) but they are free to choose the quality level and the amount of services to provide.[4] This implies that the quality and quantity of health care might vary across Regions. Regions are free to provide non-LEA services, but they must be financed with resources raised autonomously. Since the patients' right to refer themselves to any hospital has not been limited so far, in the emerging environment publicly financed hospitals, including those run by the LHAs, are strongly motivated to invest in quality and to establish a good reputation in order to attract patients and to generate a stable cash flow.

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[2] A portion on national income taxes (the IRPEF) was transferred to regions (the regional IRPEF), and health insurance contributions were replaced by regionally collected taxes on the value added by companies and on the salaries of public sector employees (the IRAP)

[3] The National Solidarity Fund has been introduced in order to allow fiscal equalization across regions; it is financed by funds coming from central government.

[4] The bunch of LEAs was defined on the basis of effectiveness, appropriateness and efficiency criteria.

We would expect patient mobility to cause expenditure uncertainty for the LHAs' planners, at least in the short term, since it is hard to predict. Regions providing treatments to patients who are resident in other Regions receive financial compensation for the treatment offered. National tariffs, which are DRG-based, are used to fund interregional patient flows. It is likely that Regions providing fewer and lower quality health care services have to pay the regions providing more services (which are probably the richer ones) because of the treatment received by mobile patients. This mechanism could create deep and long lasting imbalances across regions and bring rationing of health services to patients living in the poorest regions. For these reasons, we believe that it is important to analyse the determinants of patient mobility.

Patient mobility is partly unavoidable. It would be inefficient to provide more specialized or very rare treatments at every hospital. On the contrary, it is efficient, to some extent, to concentrate their production in a few centres. Apart from these treatments, it makes sense to consider the decision to move as the manifestation of dissatisfaction for the local supply of health care, as suggested by Tiebout's "voting with the feet" mechanism. In this paper, we are not going to formulate considerations about the welfare consequences of patient mobility, but we aim to provide some insights into the determinants of this behaviour in order to let health care planners make more informed policy decisions.

3 THE GEOGRAPHY OF HOSPITAL ADMISSION IN THE ITALIAN NHS

3.1 MOBILITY FLOWS DATA

We analyse patient mobility across Italian LHAs using data on hospital admissions that occurred in all public hospitals during the year 2001. Patient flows are reported in an origin/destination matrix provided by the Italian Ministry of Health. For each DRG the matrix reports the flows of patients occurring between each pair of origin-destination LHAs, where the origin refers to the LHA where the patients are enrolled in, and the destination refers to the LHA where the patients receive the hospital treatment. In the reference year, the Italian territory is partitioned into 197 LHAs. However, only 190 LHAs are present in our dataset due to the fact that we were forced to aggregate those LHAs operating in a single municipality.[5] Given the huge demographic dimension of these artificial LHAs we opt for excluding them from the analysis. Moreover, we disregard all the flows generated and directed to the LHAs of Sardinia and Sicily. These two regions are islands and the patient flow to and from them may follow peculiar patterns. We end up with a set of 171 LHAs.

[5] The municipalities of Turin and Rome comprise 4 and 5 LHAs, respectively.

To provide a comprehensive and significant analysis of mobility patterns in hospital admission, while maintaining manageability, we reduce the dimension of the matrix by aggregating the DRGs into 7 broad groups (PRODUCT). In order to account for different patient severity we consider the following groups of clinical procedures and/or conditions: complex surgery (CS), emergencies (EM), cancer (CA), HIV, delivery (DE), basic surgery (BS) and basic medicine (BM). **Table A1** of the appendix details the aggregation. The market shares of these categories vary significantly the larger being BM (47.6%) and BS (23.6%), and the smaller ones complex surgery (1.7%) and HIV (0.5%).

In the following analysis, we disregard the HIV, DE and EM products. There are too few HIV cases to make the analysis reliable for this product. For EM, patient flows tend to be affected by "occasional mobility". This kind of mobility is hardly attributable to a deliberate patient's decision, but to the need of a hospital admission when far from home for holiday or work. Finally, concerning DE, we notice that patients naturally tends to gravitate around the place of residence, with little or almost none mobility, or to the place where the family of origin lives, thus leading to temporary residential relocation.

3.2 SUMMARY INDICATORS OF PATIENT MOBILITY IN ITALY

Our preliminary analysis is based upon a set of summary indicators of patient flows across the LHAs. We consider the following indicators, each computed for the 4 products considered in our study and reported in Table 1:

- Exit rate: the share of hospital admissions received by LHA enrolees outside that LHA.
- Inflow rate: the share of hospital admissions in a given LHA that are provided to non-enrolees.
- Accessibility: the average distance travelled by the enrolees in a given LHA to receive hospital treatments outside their LHA. It measures the radius of the search area for hospital care and therefore proxies the private costs of mobility suffered by enrolees to receive hospital treatments at the chosen admitting hospital.
- Attractiveness: the average distance travelled by non-enrolled patients admitted to hospital in a given LHA. It gives a measure of the radius of the catchment's area for the hospital care supplied by a LHA. The higher this value the higher is the ability of the LHAs supply to attract outside patients.

INSERT TABLE 1 ABOUT HERE

According to our data exit rates are larger from LHAs located in south of Italy, while inflow rates does not exhibit any regional variation. Accessibility is remarkably poorer for enrolees of southern LHAs, namely almost 200 km vis-a-vis less than 90 for those enrolled in the remaining LHAs. Attractiveness is larger for LHAs in the North-West. It is apparent that search areas are larger in the South while, at the same time, catchment areas are smaller there. Overall this evidence suggests that the distribution of flows is uneven across Italy. If mobility is a “defensive strategy” in face of bad quality, this pattern clearly suggests that hospital care in the south of Italy is less satisfactory to enrolees that the one provided in the rest of the country.

Exit and inflow rates are quite large for the infrequent treatments included in complex surgery, (almost 60% and 30% respectively), being rather small for basic medicine (about 20%). Average distance travelled to get the required hospital admission is about 105 km for basic medicine, 102 for basic surgery, 117 for cancer and 146 for complex surgery. Quite surprisingly we notice that catchment areas for LHAs hospital supply are smaller for complex surgery and larger for basic medicine.

Finally as far as the size of the pool of enrolees is concerned we notice that exit rates are larger in smaller LHAs, inflow rates being almost invariant. Search areas and catchment areas seem wider the bigger is the LHA.

In order to go beyond descriptive statistics and gain some insights into the factors behind the observed mobility patterns we need to adopt a modelling framework allowing us to control for distance, contiguity, and supply characteristics. To that aim we rely upon the estimation of gravity models for patient flows. After a review of the most relevant literature related to gravity models and hospital choice, the remaining part of the paper details our empirical strategy.

4 LITERATURE REVIEW

4.1 GRAVITY MODELS

For our study we will adopt the framework of the gravity models. The social gravity model of spatial interaction has been developed as an analogy to the Newtonian gravity model of Physics. In this model it is hypothesized that a greater level of spatial interaction should occur between two points in space the greater are the two population masses at those points and the lesser is the spatial distance between them (Stewart, 1948).

An important distinction we have to consider is between the so called “push” and “pull” factors influencing the aggregate flows. The former are the elements of “propulsiveness” of an area (the characteristics of an area that make the residents want to exit that area) and the latter are the elements of “attractiveness” (the characteristics that make the area appealing).

4.2 HOSPITAL CHOICE

We believe it is important to consider the past literature on hospital choice models in order to be aware of the main variables that can influence patient choice and how they influence it. This analysis allows us to form some expectations about the signs with which these variables will enter into our gravity equation.

The variables that are considered most may be grouped under some categories: distance, hospital characteristics, area characteristics, and individual characteristics.

DISTANCE

Earlier studies on patients’ choice of hospital have already focused on distance to the hospital facilities, highlighting the “distance decay” pattern phenomenon: people tend to use the service of closer, over more distant, health providers so that the number of persons using particular providers declines at greater distance (Bashshur et al., 1971; Morill and Earickson, 1968; Morrill et al., 1970; Roghmann and Zastowny, 1979; Studnicki, 1975). In general, distance has been widely recognised as a powerful predictor of hospital choice (Basu and Friedman, 2001; Burns and Wholey, 1992; Dranove and Shanley, 1989; Goodman et al., 1997; Seniger, 1999; Tai et al., 2004; Tay, 2003)[6]. More recently, other variables, such as travel time and travel costs, have been used instead of distance in order to represent the difficulty for the patient in reaching the hospital. They have also been shown to negatively affect the probability of choosing the hospital (Bessho, 2003; McNamara, 2003; Varkevisser and van der Geest, 2006).

HOSPITAL CHARACTERISTICS

Between the various hospital characteristics the quality of the hospital is usually taken into consideration. Variables capturing hospital quality include both input and output measures. Between the more used input measures, there are number of nurses/doctors per bed (McNamara, 2003; Tay, 2003), the range of specialized services offered (Tai et al., 2004); and teaching status (Basu and Friedman, 2001; Burns and Wholey, 1992; Goodman et al.,1997; Tay, 2003), while between the more popular outcome measures, there are mortality rates (Burns and Wholey, 1992; Tay, 2003) and complications of the patients admitted to the hospital (Tay, 2003). There is strong evidence showing that patients tend to choose higher quality hospitals.

[6] In studies where the physician is considered the decision maker, the distance of the physician to the hospital is often considered and it is found to negatively influence admission to the hospital (McGuirk and Porell, 1984; Burns and Wholey, 1992).

These variables are often hard to measure and if just considered individually could be misleading. As outlined by Tay (2003), the use of patient outcomes as a proxy for quality is complicated for two reasons. Firstly, outcome measures can be very noisy, especially if considered for hospitals with low patient volume. Secondly, a selection bias problem could arise: good quality hospitals could attract sicker patients, with the higher probability of having complications or dying, and thus they may report lower outcome performance. A way to address this problem is to adjust the outcome for the differences in the case-mix of hospitals. The use of the input measures as indicators of hospital quality can be problematic, as well. To some extent, indeed, these variables represent the amount of resources that are utilized and the "effort" a hospital is putting in, but this doesn't automatically imply a good quality result. Thus, it seems very important to consider not just a single indicator, but many indicators simultaneously.

Hospital size (measured as the number of beds) is another common hospital level variable used in this literature (Goodman et al., 1997; McGuirk and Porell, 1984; McNamara, 2003; Tai et al., 2004; Tay, 2003; Varkevisser and van der Geest, 2006). It is often considered as a proxy of hospital quality and it positively affects the probability of choosing the hospital. As stressed by Varkevisser and van der Geest (2006), the use of this variable may raise a problem of endogeneity: is it the larger hospital size that increases the likelihood of selecting that hospital, or do the high selection rates lead to the larger hospital size?

Some recent studies have considered waiting times as a relevant hospital characteristic that may influence patient choice (Bessho, 2003; Varkevisser and van der Geest, 2006). Low levels of waiting time seem to strongly attract patients.

AREA CHARACTERISTICS

Some studies have tried to take into consideration how the characteristics of the area where people live could affect hospital choice. Some studies have considered metropolitan vs. non-metropolitan areas, and rural vs. urban (Basu and Friedman, 2001; Goodman et al., 1997; Varkevisser and van der Geest, 2006). The evidence from these studies is mixed. For example, in the study by Goodman et al. (1997) belonging to a rural area does not significantly affect the probability of referring to a hospital further away, while in the study by Basu and Friedman (2001) a patient's residence in a rural county adjacent to a metropolitan area increased the likelihood that they would cross the county boundary. Other studies have considered median household income (Basu and Friedman, 2001; Goodman et al., 1997), showing that a high level of this variable increases the probability of referring to a hospital further away.

A critical issue in the hospital choice model regards the definition of the areas to consider as geographic entities. Arbitrary jurisdictional geographic boundaries (e.g., counties or zip code clusters) are often used in order to define the market in which the hospitals are operating, without checking the consistency of market area definitions adopted with the economic principles and/or the more accepted methods for deriving market definitions. Our choice of using the LHA as the geographical area of reference seems the most appropriate choice in relation to the Italian context. As mentioned above, indeed, the LHAs are the administrative entities with significant managerial autonomy at the lowest level of the organization of the Italian NHS.

INDIVIDUAL CHARACTERISTICS

Among individual level characteristics, the most common ones included in the studies are gender, age, education, race, income, insurance status (Basu and Friedman, 2001; Bessho, 2003; Goodman et al., 1997; Tai et al., 2004). In general, women and old people are less likely to travel long distances to receive hospital services, but the results are not conclusive. High levels of personal income and belonging to the white ethnic group seem to increase the probability of referring to hospitals further away.

A very important variable considered by many studies is the severity of the conditions of the patients referring to the hospitals. Most of the authors dealing with this issue develop their analysis by considering DRGs of different severity separately, for example orthopaedics vs. neurosurgery (Basu and Friedman, 2001; Goodman et al., 1997; Tai et al., 2004; Varkevisser and van der Geest, 2006), while others consider whether the health conditions of the patients are life threatening or not (McNamara, 2003). This variable has been proved very significant for the choice of hospital. The literature, indeed, suggests that there is a wide consensus that willingness to pay for referring to higher quality hospitals further away is significantly higher for patients with more severe conditions.

4.3 PATIENT MOBILITY AND THE GRAVITY APPROACH

Some papers have recently dealt with the patient mobility phenomenon by developing a gravity model. Congdon (2001) models patient flows to emergency units and describes how such models may be adapted to allow for unit closures and expansion, or the opening up of other units. The paper deals with five boroughs in North East London (part of North Thames Health Region) and an adjacent LHA in Essex, where the total resident population (1991 Census) was 1.1 million. This area has been subdivided into 127 electoral wards, and the analysis relates to 84,500 patient flows (resulting in inpatient admissions) from these small areas of residence to eight hospitals with emergency patient facilities. The estimation of the gravity model is based on simulation based Bayesian methods. The main regressors are the distance from the hospital, the population and the hospital mass (in terms of number of beds).[7] The first regressor negatively affects the hospital inflows, while the other two positively affect inflows.

Levaggi and Zanola's (2004) study the relationship between the number of people moving from one region to another, the quality of the service offered and to the distance between regions. The structure of the empirical specification of the cross-migration measure is the following:

$$\mu_{ir} = \alpha_0 + \alpha_1 \left(\frac{y_i}{y_r} \right) + \alpha_2 z(.) + \varepsilon_i$$

where μ_{ir} = net patient flow, i.e. inflows – outflows, from each region (i is the region of origin or the flow while r is the rest of Italy), y_i = per capita income in region i, y_r = national per capita income, z(.) = function of relative regional hospital quality attributes of the region and the rest of Italy and ε_i is the error term.The regressors considered in the models are per capita income, the percentage of people aged over 65 years (considered as a proxy of the regional need of health care) and hospital quality, measured in terms of structure indicators (number of beds for 1000 people, number of hospitals for 1000 people, public expenditure at regional levels in nominal values), outcomes indicators (ratio between the number of inpatients and the number of beds) and process measurement (index of turnover). The dataset used is made up of a sample of panel observations covering regional mobility and other indicators over the period 1994-1997. The assumption of fixed coefficients over time and over cross-section units has been checked through an F-test. Since the null hypothesis of equal coefficients for each year could not be rejected the data are considered as a pool. All the regressors (apart from the number of beds for 1000 people and regional expenditures) are statistically significant. The authors find that per capita income has a positive impact on inflows (thus it has to be interpreted as ability to pay for quality at the regional level), older people seem less prone to travel and the quality variables have a positive impact on the net inflow of patients.

5 ECONOMETRIC MODEL AND ESTIMATION

In our empirical analysis we adopt a macro approach to the modelling of aggregated flows, developing an "unconstrained" model for patient mobility across LHAs. This class of spatial interaction models allows for a flexible analysis of the interplay between pushing and pulling factors at the price of a low predicting power. We assume that, for each product examined in our analysis, the observed matrix of pair-wise flows is determined, in its simplest form, by the following equation:

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[7] In an extension of the model the author also considers the health needs (measured by the York Acute Needs score) and the percentage of the population aged over 65.

$$m_{ij} = \alpha_0 push_i^{\alpha_1} \times pull_j^{\alpha_2} \times f(d_{ij}, k_{ij}) \times \eta_{ij} \qquad (1)$$

where m_{ij} is the number of patients enrolled in LHA$_i$ that receive a hospital treatment in LHA$_j$, $push_i$ and $pull_j$ represent a push and a pull factor in origin LHA$_i$ and in destination LHA$_j$ respectively, f is the spatial deterrence as a function of the distance between LHA$_i$ and LHA$_i$, d_{ij} , and pair-specific impeding factors other than distance, k_{ij}, and η_{ij} is an error term with $E(\eta_{ij} | push_i , pull_j , d_{ij}, k_{ij}) = 1$ assumed to be statistically independent of the regressors.

As far as the empirical estimation of the gravity models is concerned, there is a long tradition in the literature of making a log-linearization of them and using OLS to estimate the parameters of interest. This procedure is appealing because is very simple. However it fails to work when no flow is observed between some pairs of origin and destination thus making the dependent variable a true zero (Porell and Adams, 1995; Stilwell, 2005). Several methods have been adopted to deal with log-linearization of the zero observations. In a number of studies the pairs with null flows have just been dropped from the dataset. Others have used a Tobit estimator. Rather than throwing away observations with zero flows, some authors have attributed the value of 1 to these observations. For a more complete description of the various procedures see Frankel (1997). These procedures will generally lead to biased estimators for the parameters of the model, the bias being particularly severe when the proportion of zero flows is large.[8] Moreover, as pointed out by Santos-Silva and Tenreyro (2006), when the error term in the log gravity equation is heteroskedastic, the OLS regression leads to inconsistent estimates. The expected value of the logarithm of a random variable depends both on its mean and on the higher-order moments of the distribution. Hence, if the variance of the error term in the gravity equation depends on the regressors, the expected value of the logarithm of the error term will also depend on the regressors, violating the condition of consistency of OLS.

To address these two problems we follow the proposal by Santos-Silva and Tenreyro (2006) and estimate model (1) using a PML estimator (see McCullagh and Nelder, 1989) based on the assumption that the conditional variance is proportional to the conditional mean.[9] Under this assumption the parameters of the model can be estimated by solving a set of first-order conditions numerically equal to the Poisson pseudo-maximum-likelihood (PPML) estimator. Thereafter the empirical implementation of the PPML estimator is straightforward provided that there are standard

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[8] Santos-Silva and Tenreyro (2006) provide a clear picture of the magnitude of this bias.

[9] For the sake of completeness, we underline that the Poisson regression has already proposed in the literature as a way to address the problem of zero flows (See for instance, Goodman et al. (1997)). However, to our knowledge, Santos-Silva and Tenreyro (2006) are the first ones to use this method to address the issue of heterogeneity.

econometric programs with commands for the estimation of Poisson regression. All that is needed for this estimator to be consistent is the correct specification of the conditional mean, that is, $E\left(m_{ij} \middle| push_i , pull_j , d_{ij} , k_{ij}\right) = \alpha_0 push_i^{\alpha_1} \times pull_j^{\alpha_2} \times f(d_{ij}, k_{ij})$. In case the assumption that the conditional variance is proportional to the conditional mean does not hold (which is often the case), the estimator does not fully account for the heteroskedasticity in the model. For this reason, the inference has to be based on an Eicker-White robust covariance matrix estimator (Eicker, 1963; White, 1980).

6 DATA AND MODEL SPECIFICATION

Our dependent variable is the number of patients admitted to hospital that flow from each LHA of origin to each possible LHAs of destination. We focus here only on those patients that seek care outside the LHA they are enrolled in. Therefore our analysis is akin to a standard gravity model of trade. Since, as we mentioned earlier, our dataset comprises 171 LHAs, a typical origin\destination matrix contains 29070 pairs (observations). Table 2 provides some detail on the dependent variable considered in this piece of work.

INSERT TABLE 2 ABOUT HERE

Our preferred specification emerged out of an extensive specification analysis we conducted using several other controls we do not detail here and considering various forms for the link function.[10] Our search was basically driven by the correct specification of the conditional mean. This was tested by way of the RESET test (Ramsey, 1969) and the LINK test (Pregibon, 1980). The former is performed by computing the linear prediction from the regression function, squaring those values, and estimating again the original model adding this new variable to the list of regressors. If this variable is not significant then the model should be considered correctly specified. The LINK test is performed by regressing the dependent variable on the linear prediction from the estimated regression function and on its squared value. The test is based on the coefficient for this last term: if significant then the original model is likely misspecified.

Although the PPML estimator is consistent even if the variance function is not well specified, we test also for the specific pattern of heteroskedasticity we assumed, i.e. conditional variance proportional to the conditional mean. If we assume that the conditional variance belongs to the class

[10] A complete report on the specification analysis is available upon request.

of variance functions examined by Manning and Mullahy (2001) where $Var\left(m_{ij}|x\right)=\lambda_0 E\left[m_{ij}|x\right]^{\lambda_1}$, it is possible to estimate λ_1, by running an auxiliary Park-type regression (Park, 1966). Assuming $\overline{m}_{ij}$ denotes the estimated value for $E\left[m_{ij}|x\right]$, λ_1 can be obtained by the GLM estimation of following equation

$$\left(m_{ij}-\overline{m}_{ij}\right)^2=\lambda_0(\overline{m}_{ij})^{\lambda_1}+\xi_i \qquad (2)$$

This approach is asymptotically valid and the inference about λ_1 can be made using the Eicker-White robust covariance matrix estimator. Values of λ_1 not statistically different from 1 are consistent with our assumption that the conditional variance is proportional to the conditional mean.

In the following we discuss the variables included in our preferred specification. We organize our presentation under the headings of push\pull factors, spatial deterrence, and spatial pattern factors. Tables 3 and 4 provide some descriptive statistics for the included regressors.

INSERT TABLE 3 and 4 ABOUT HERE

6.1 PUSH AND PULL FACTORS

We are particularly interested in analysing the effects on patient flows of some LHA specific variables. The regressors included in our preferred specification are all proxies capturing the broad concept of quality in the supply of hospital care. Note that all these variables enter the model both as pushing factors (i.e. referred to the LHAs of origin) and pulling factors (i.e. referred to the LHAs of destination).

POPULATION indicates the number of enrolees of the LHA. We will consider this measure in 10,000 units. Assuming that the share of enrolees in need for a hospital admission in a given product does not vary with the size of the pool this measure proxy the demand for hospital treatments in each given product arising at a given LHA. There are good reasons to expect that the larger this demand the greater should be the possibility of reaching scale economies in hospital production and of risk sharing among the enrolees, leading to economies of scale in insurance cost. This implication has found empirical support in the analysis of Wholey et al. (1996). By way of such scale effects patients enrolled in bigger LHAs are, other things being equal, more likely to receive high quality, specialized hospital care. Since enrolment is basically defined on the place of residence, Italian LHAs are quite similar to US health maintenance organizations (HMOs) but for the absence of any adverse selection. Therefore our case study is particularly well suited for conducting an empirical test for the presence of scale effect due to the size of the pool of enrolees. We expect that the larger this pool the lower will be the outflow of patients seeking care outside and the larger the inflow of patients coming from other LHAs. According to the specification analysis population enters our gravity models either via a power function and an exponential function as follows:

$$E\left(m_{ij}\left|push_i\ , pull_j\ , d_{ij}, k_{ij}\right.\right) = \alpha_0 POP_i^{\beta_1} \times \exp(\beta_2 POP_i) \times POP_j^{\beta_3} \times \exp(\beta_4 POP_j) \times f(d_{ij}, k_{ij})$$

This formulation allows for a very convenient, flexible modelling of the elasticity of patients' flows to the number of enrolees, which takes the form (with respect to the size of enrolees at the LHA of origin):

$$\varepsilon_{POP_i} = \frac{\partial E\left(m_{ij}\left|POP_i\ , POP_j\ , d_{ij}, k_{ij}\right.\right)}{\partial POP_i} \frac{POP_i}{E\left(m_{ij}\left|POP_i\ , POP_j\ , d_{ij}, k_{ij}\right.\right)} = \beta_1 + \beta_2 \times POP_i$$

The variable INCOME PER CAPITA is measured as the after-tax income per capita available on average to individuals living in a given LHA. It is estimated using data from the Survey on Household Income and Wealth conducted by the Bank. In the literature on hospital choice income is shown to positively affect positively mobility, i.e. richer individuals are able to choose further destination. However in our aggregate spatial interaction modeling average income per capita is likely to capture broadly defined social capital effects. We expect to observe, coeteris paribus, better quality of care (one distinctive feature of social capital) in richer LHAs and therefore an emergent pattern of patients' flows moving from poorer to richer LHAs. Finally we include the DOCTORS per BED ratio defined as the number of doctors for 100 hospital beds. This is a rather commonly used characteristic in this literature on hospital choice, shown to influence negatively the outflows and positively the inflows of patients. Both these variables enter our preferred specification via a power function.

6.2 *SPATIAL DETERRENCE*

At the end of our specification analysis we reached the following specification for the deterrence function:

$$f(d_{ij}, k_{ij}) = d_{ij}^{\gamma_1 + \gamma_2 BARR_{ij}} \exp(\gamma_3 BARR_{ij}) \exp(\gamma_4 CONTIG_{ij}) \exp(\gamma_5 CONTIG_{ij} * BARR_{ij})$$

The DISTANCE (d_{ij}) between each pair of LHAs has been calculated as the Euclidean norm between LHAs' centroids.[11] Geo-referenced coordinates of the centroids were constructed from ESRI Dataset reporting geographical coordinates (in metres) for each municipality of Italy. The

[11] Other measure of distance could have been adopted in our analysis. We could have considered, for example, the "road distance" between the LHAs` centroids or the "driving time" required to travel from one LHA to another. The computation of these measures of distance, however, is more complex and requires the formulation of more assumptions (for example, travelling routes, average driving speed) than the Euclidean distance among LHAs` centroids. This also require adding data not available to our study. Therefore, we have chosen to rely on the Euclidean measure as a more objective measure of distance.

variable was finally expressed in 10 kilometres. Other things being equal, distance should capture the deterrence effect on patients' flows due to direct and indirect cost of mobility. Distance enters our preferred specification of the conditional mean via a power function. CONTIGUITY is a dummy variable assuming a value of 1 when the origin and destination LHAs share a border, and 0 otherwise. This variable is often included in the gravity models as a trade facilitator since contiguity leads to complementary specialization patterns among trading entities. This variable assumes a peculiar value in our case study. As a matter of fact it is common practice in the Italian NHS to arrange special agreements between contiguous LHAs to handle the problems posed by excess mobility. Finally, the dummy BARRIER, assuming a value of 1 if the “trading” LHAs belong to different regions, and 0 otherwise, is to be intended as a control for the presence of “institutional barriers” that can affect patient flows.

6.3 CONTROLS FOR SPATIAL PATTERNS

To control for peculiar patterns in the geography of hospital admission in Italy we inserted a set of spatial controls. In our specification analysis we tried several combinations of these controls (also a full set of regional dummies) ending up with the preferred specification including only REMOTENESS and a proxy for LATITUDE. The variable REMOTENESS is defined as the mean distance (in 10 kilometres) of each LHA from all other LHAs, weighed by the number of enrolees of each LHA. We control for REMOTENESS to allow for the hypothesis that larger distances to all other LHAs might increase, other things being equal, bilateral flows between two LHAs. We expect, coherently with evidence in the empirical literature on trade, this variable to affect positively patient flows (see Deardoff, 1998). This point is clarified by Santos-Silva and Tenreyro (2006) when they notice that the most remote countries (LHAs) will tend to trade more between each other because they do not have alternative trading partners (on this point, see also Congdon, 2001). It is well accepted (see Japelli, Pistaferri and Weber, 2007) that the gradient of healthcare quality in Italy, declines from north to south. Our proxy for LATITUDE aims at capturing the implications that originate from this stylized fact. It is defined as the distance (in 10 kilometres) of each LHAs from the LHA that lays most in the north. Therefore this proxy captures how far in the south of Italy lays a given LHA. Overall we expect it to affect positively the outflows of patients and negatively the inflows.

Both these variables enter our preferred specification via a power function.

7 RESULTS

Table 5, reports our estimates of the preferred gravity models specification for patients flows in each considered product: complex surgery, cancer, basic surgery and basic medicine.

INSERT TABLE 5 ABOUT HERE

All the estimated models pass the LINK test with the notable exception of the one for complex surgery. This one is most likely considered "on the edge of rejection" (the p-value of the test being 0.041). According to the RESET test however the model for complex surgery is clearly to be considered as misspecified. Concerning the particular pattern of heteroskedasticity assumed for our Poisson PML, i.e. conditional variance being proportional to the conditional mean, our Park-type test cannot reject it even at very low significance levels. Therefore, by considering the overall results of our specification tests, we believe that our gravity model provides an adequate frame to explain the patient mobility in our case for cancer, basic surgery and basic medicine, but not for complex surgery. For this reason, despite in the rest of the paper we present results also for this last product we will abstain from commenting them.

Since we are dealing with a non-linear model, only some of the coefficients presented in Table 5 are clearly interpretable. Income, docs-to-beds ratio, remoteness and latitude enter the specification via a simple power function therefore their estimated coefficients are interpretable as (constant) elasticities. It is worth noticing that, when significant, the sign of these elasticities are those we expected. In particular we notice that the elasticity of outflows to income is about -3.2/-3.8 while the corresponding inflow elasticity is almost 6 for cancer, 5 for basic surgery and 4.1 for basic medicine. This evidence suggests that a 10% increase in available income reduces the patients' outflows from a LHA by more than 30% while it increases quite dramatically the inflows (between 40% to 60%). It is therefore quite clearly proved by our analysis that, other things being equal, in Italy patients tend to flow from poorer, less developed LHAs to richer, better endowed ones, in particular for the more severe caseload of patients with cancer..

The impacts attributable to population and arguments of the deterrence function can be evaluated provided we estimate appropriate marginal effects and elasticities.

Figure 1 and 2 plot the estimated outflow and inflow elasticities to the size of the pool of enrolees for each LHA in our sample. To interpret an outflow elasticity let's notice that it represents the relative variation of $\frac{m_{i\bullet}}{POP_i}$ where $m_{i\bullet}$ is the total outflow of patient from LHA *i*. Assuming that the share of enrolees in need for a hospital admission in a given product does not vary with the size of the pool this ratio is informative on how dependent is LHA's demand on the supply from external providers. Similarly, inflow elasticity is the relative variation of $\frac{m_{\bullet j}}{POP_j}$, with $m_{\bullet j}$ as the total inflow of patient to LHA j, the ratio being the share of external to internal demand for LHA hospital supply.

INSERT FIGURES 1 and 2 ABOUT HERE

According to our estimated models outflow elasticities are declining along the whole range of sizes and assume positive values for small LHAs, turning to negative, but not significantly different from zero, values once a certain dimension is reached. This evidence implies that LHA's demand for hospital treatments become less dependant on the supply from external providers as its size increases. After a given size is reached the total outflows of patients does not increases with the total demand. We evaluate that this size is above 400 thousands enrolees for cancer, about 500 thousands for basic surgery and approximately 600 for basic medicine.

Coming to inflow elasticities, it is worth noticing that a unit elasticity would imply that the exports-to-internal demand ratio does not change with the size of the pool of enrolees. Values below (above) 1 imply that exports increase at a slower (faster) rate than internal demand. In our case inflow elasticities are always positive and, more remarkably, increasing along the whole range of sizes going from values below 1, for the smaller LHAs to values close or above two for the bigger ones. This implies that the share of export-to-internal demand for LHA hospital care follow a U-shaped curve with a minimum at about 300 thousands enrolees for cancer, and about 500 for basic surgery and basic medicine.

Table 6 reports marginal effects and relative marginal effects, estimated at the sample mean, for arguments entering the deterrence function. As expected, CONTIGUITY exerts a positive marginal effect on patient flows which is relatively larger for flows directed to LHAs out of region than for those remaining within the regional border. It is worth noticing that the effect of contiguity is relatively larger the less complex is the hospital treatment considered. This pattern is particularly pronounced in the case of flows directed towards extra regional destinations. For extra regional flows in basic medicine contiguity results in an increase that is 5.5 times the baseline flow directed to non contiguous LHAs. The corresponding figure is 3.6 for basic surgery and only 1.9 for cancer. This pattern suggests that contiguity strengthen more the competition for attracting the demand originating outside the region than that originating within the same region. In a way contiguous LHAs belonging to the same region compete less fiercely to attract patients one from the other than those belonging to different regions. Moreover contiguity strengthen competition the more in basic medicine.

INSERT TABLE 6 ABOUT HERE

Looking at the impact of institutional BARRIER we notice that it exerts a negative marginal effect which is of the same relative magnitude irrespective of contiguity. In a way contiguity is of no help in making barrier less insurmountable. The deterrence effect of institutional barrier is clearly larger the more complex is the hospital treatment. Crossing the regional border reduces patient's outflows in cancer product by an amount that is .9 times the baseline flow directed to regional destinations. The corresponding relative reductions are smaller for basic surgery and basic medicine.

8 FINAL REMARKS

The geography of hospital admissions in Italy raises policy concerns for issues related to equity of access and financial sustainability. Patients' right to choose the admitting hospital undermines financial stability of enrolling LHAs. Since the quality of hospital care is not evenly distributed across the country, patients take advantage of their right referring to better quality providers, even outside their enrolling LHAs. Provided reimbursements follow the patients, funds therefore tend to outflow from LHAs "importing" hospital services to those that "export" them. This situation leads to an uneven distribution of private mobility costs and promote the accumulation of financial resources towards the already better endowed LHAs. In this paper we aimed at evaluating to what extent the observed imbalances in the Italian geography of hospital admission are due to scale effects or reflect the working of other spatial factors in the distribution of healthcare resources.

We work on an origin/destination matrix comprising all ordinary admissions to public hospitals in Italy during the year 2001. To control for distance, contiguity, and supply characteristics, we estimate a gravity equation for the full matrix of pair-wise flows as grouped into 4 broad diagnostic products. We estimate gravity equations adopting a Poisson pseudo maximum likelihood approach, a method that is robust to different patterns of heteroskedasticity and provides a natural way to deal with the zero flows.

Our results suggest that the gravity model is a good framework for explaining the patient mobility phenomenon for most of the examined diagnostic groups. Our evidence suggests that the ability to contain the imports of hospital services from other LHAs increases with the size of the pool of enrolees. Moreover we find that the ability to export hospital services, as proxied by the ratio of export-to-internal demand, is U-shaped. Therefore our evidence suggests that there are scale effect played by the size of the pool of enrolees. Since funds accrue to LHAs on a capitation basis, and smaller LHAs is relatively less likely to contain patients' outflows while receiving smaller inflows, this policy variable is crucial in determining LHAs financial stability. A natural way to deal with these issues is to adjust resource allocation formulas, namely the capitation rule, to account for the size of the pool.

The analysis conducted so far has some limitations.

In our econometric specification we did not include LHA fixed effects. Anderson and van Wincoop (2003) argue that the traditional gravity equation suffers from a problem of omitted variable since it does not take into account the multilateral resistance term, which is very relevant in trade. Following these authors, many recent studies estimating a gravity equation include importers and exporters fixed effects as regressors in order to take into account the presence of these multilateral resistance terms (for instance Cheng and Wall, 2004; Egger and Pfaffermayr, 2004; Westerlund and Wilhelmsson, 2006; de Frahan and Vancauteren, 2006). The problem with the inclusion of “importer” and “exporter” fixed effects is that working with cross-sectional data the identification of the effects for importer or exporter specific characteristics is precluded.

Some authors have addressed this issue by exploiting the panel nature of their data. For example, Egger and Pfaffermayr (2004) estimate a linear gravity model with fixed effect using the Hausman and Taylor (1981) estimator. Others have modelled the importer and exporter individual effects as random (uncorrelated) effects instead of fixed (correlated) effects (de Frahan and Vancauteren, 2006). Others, like Wei and Frankel (1997), have not included individual dummies in their gravity model. Including individual dummies would have undermined the efforts taken to estimate the effects of the variables that do not have variability over time (or other dimensions). In our paper we take a position similar to Wei and Frankel (1997) and adopt the traditional gravity equation, which does not include "individual effects". Since we are mainly interested in studying the effects of the LHAs’ populations on patient mobility, we do not include any LHA dummy variables, because their presence would not allow the study of the main effect of interest.[12]

[12] We underline that the main aim of Anderson and van Wincoop’s (2003) paper is studying the trade border effect and for their research hypothesis it does not matter if they cannot estimate individual specific variables.

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TABLES AND GRAPHS TO BE INCLUDED IN THE MAIN TEXT

TABLE 1: Performance measures

	Exit rate	Inflow rate	Accessibility	Attractiveness	# obs.
OVERALL	27%	21%	105.4	95.8	171
By REGION					
North-West	25%	20%	76.3	107.0	39
North-East	24%	22%	63.4	92.9	45
Centre	24%	21%	90.0	90.4	36
South	36%	22%	196.6	94.5	51
By PRODUCT					
Base Medical	22%	18%	105.3	102.8	171
Base Surgery	33%	27%	101.8	85.4	171
Cancer	38%	23%	117.0	89.4	171
Complex Surgery	58%	30%	136.2	80.4	171
By #ENROLLEES					
less than 150	29%	23%	98.9	83.1	44
150 - 250	28%	20%	92.6	97.5	57
250 - 400	23%	23%	126.6	98.2	41
more than 400	26%	20%	111.0	108.0	29

TABLE 2: Descriptive statistics: dependent variable

	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
MEAN Patients' flows (all flows)	2.8	4.3	14.3	23.4
SD Patients' flows (all flows)	29.2	47.6	130.2	237.8
% positive flows	0.18	0.20	0.45	0.61
# positive flows	5070	5674	13207	17775
MEAN Patients' flows (positive flows)	15.9	22.2	31.4	38.2
SD Patients' flows (positive flows)	67.8	105.8	191.7	303.2

TABLE 3: Descriptive statistics: regressors

Variable	Mean	Std. Dev.	Min	Max
Push/pull factors				
Log population at origin/destination LHA	12.31	0.67	9.57	14.08
Population at origin/destination LHA	27.78	20.86	1.43	130.16
Log income per capita at origin/destination LHA	2.12	0.15	1.71	2.34
Log docs-to-beds ratio in the origin/destination LHA	1.43	0.28	-0.16	2.35
Spatial deterrence				
Log distance	5.72	0.77	2.22	7.01
Contiguity dummy	0.03	0.17	0.00	1.00
Institutional barrier dummy	0.93	0.25	0.00	1.00
Log distance for out of region flows	5.45	1.59	0.00	7.01
Contiguity dummy*Institutional barrier	0.01	0.10	0.00	1.00
Spatial patterns				
Origin/destination LHA's remoteness	5.99	0.18	5.73	6.46
Origin/destination LHA's log distance from the north	5.62	0.91	0.00	6.85

TABLE 4: Descriptive statistics on spatial deterrence factors: positive flows

	Mean	Std. Dev.
COMPLEX SURGERY (# obs. 5070)		
Log distance	5.18	1.01
Contiguity dummy	0.14	0.34
Institutional barrier	0.77	0.42
Log distance for out of region flows	4.26	2.45
Contiguity dummy*Institutional barrier	0.04	0.19
CANCER (# obs. 5674)		
Log distance	5.21	1.03
Contiguity dummy	0.14	0.35
Institutional barrier	0.77	0.42
Log distance for out of region flows	4.29	2.47
Contiguity dummy*Institutional barrier	0.04	0.20
BASIC SURGERY (# obs. 13207)		
Log distance	5.47	0.90
Contiguity dummy	0.06	0.25
Institutional barrier	0.86	0.35
Log distance for out of region flows	4.89	2.09
Contiguity dummy*Institutional barrier	0.02	0.14
BASIC MEDICINE (# obs. 17775)		
Log distance	5.59	0.86
Contiguity dummy	0.05	0.21
Institutional barrier	0.89	0.31
Log distance for out of region flows	5.15	1.90
Contiguity dummy*Institutional barrier	0.02	0.12

TABLE 5: Model estimates on the reduced set of pairwaise flows

VARIABLES	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
Log population at origin LHA	0.267*	0.741***	0.782***	0.621***
	0.071	0.000	0.000	0.000
Population at origin LHA	-0.009**	-0.013***	-0.013***	-0.006
	0.041	0.000	0.000	0.105
Log population at destination LHA	1.013***	0.298**	0.071	0.228*
	0.000	0.046	0.480	0.063
Population at destination LHA	0.008**	0.022***	0.018***	0.014***
	0.019	0.000	0.000	0.000
Log income per capita at origin LHA	-3.409***	-3.757***	-3.248***	-3.453***
	0.000	0.000	0.000	0.000
Log income per capita at destination LHA	9.444***	5.819***	4.854***	4.121***
	0.000	0.000	0.000	0.000
Log docs-to-beds ratio in the origin LHA	-0.204	-0.506***	-0.365***	-0.441***
	0.198	0.000	0.000	0.000
Log docs-to-beds ratio in the destination LHA	0.663***	0.619***	-0.038	0.076
	0.000	0.000	0.731	0.536
Log distance	-0.904***	-0.764***	-0.973***	-1.028***
	0.000	0.000	0.000	0.000
Contiguity dummy	0.895***	0.947***	1.283***	1.315***
	0.000	0.000	0.000	0.000
Institutional barrier	0.670	3.412***	1.988***	-0.126
	0.357	0.000	0.000	0.835
Log distance for out of region flows	-0.504***	-1.047***	-0.704***	-0.218
	0.001	0.000	0.000	0.105
Contiguity dummy*Institutional barrier	0.246	0.130	0.245	0.554***
	0.333	0.568	0.132	0.001
Origin LHA's remoteness	1.253***	1.796***	1.668***	0.571***
	0.000	0.000	0.000	0.010
Destination LHA's remoteness	0.994***	0.085	-0.365	0.719***
	0.003	0.840	0.151	0.003
Origin LHA's log distance from the north	0.447***	0.914***	0.624***	0.352***
	0.001	0.000	0.000	0.000
Destination LHA's log distance from the north	0.356***	-0.232***	-0.210***	0.160*
	0.001	0.004	0.004	0.061
Constant	-41.377***	-26.979***	-15.864***	-13.862***
	0.000	0.000	0.000	0.001
Observations	26625	27357	28955	29041
LINK test p-values	0.041	0.244	0.333	0.852
RESET test p-values	0.000	0.108	0.047	0.697
PARK test p-values	0.291	0.818	0.948	0.908

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. We estimate these models on a slightly reduced set of observations obtained by purging out those destinations (LHAs) that never received any inflow of patients.

Figure 1

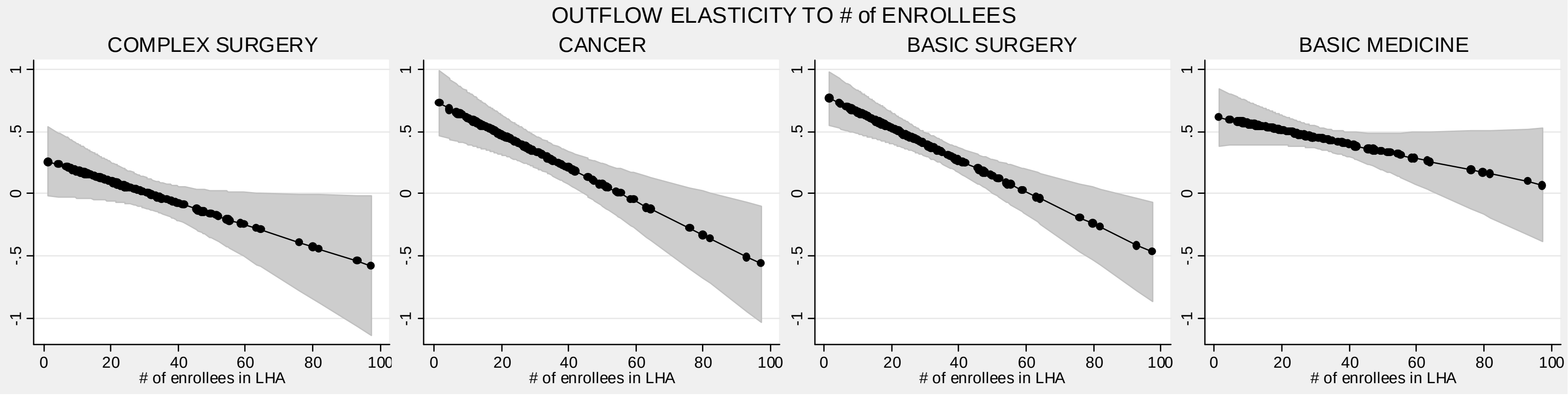

Figure 2

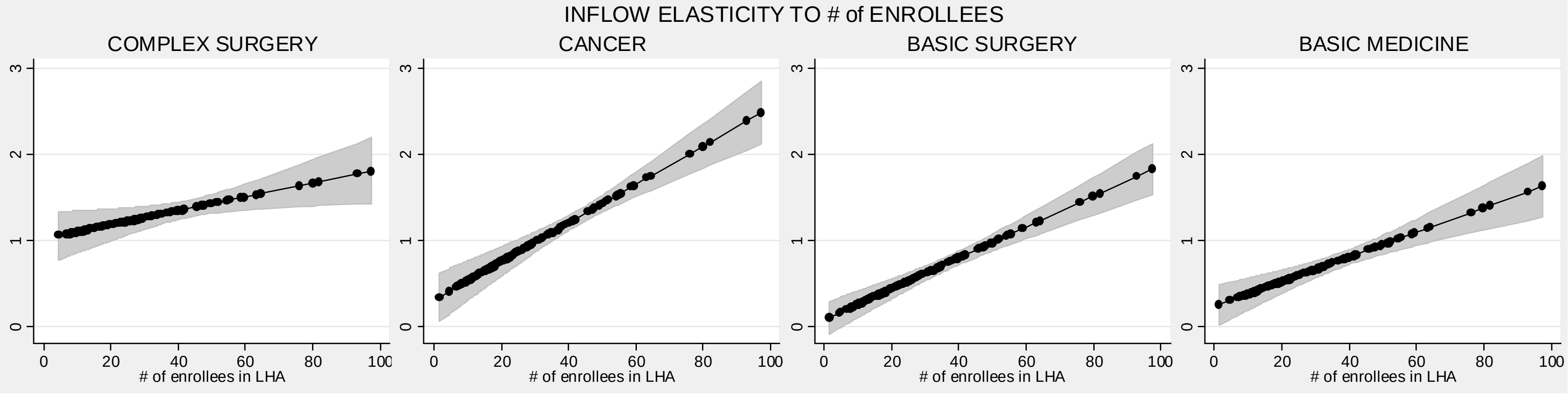

Table 6: Marginal effects and elasticities.

	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
	Marginal Effect				Relative Marginal Effect			
Contiguity for INTRA Regional flows	3.23	6.92	23.20	31.27	1.45	1.58	2.61	2.73
	(1.25)	(2.77)	(6.22)	(10.28)	(0.39)	(0.39)	(0.41)	(0.49)
Contiguity for EXTRA Regional flows	0.57	0.70	4.36	16.35	2.13	1.93	3.61	5.49
	(0.18)	(0.20)	(0.79)	(2.40)	(0.65)	(0.53)	(0.56)	(0.77)
Barrier for CONTIGUOUS LHAs	-4.84	-10.42	-27.89	-31.73	-0.86	-0.91	-0.83	-0.56
	(1.51)	(3.55)	(7.08)	(11.12)	(0.05)	(0.03)	(0.05)	(0.13)
Barrier for NOT CONTIGUOUS LHAs	-1.98	-4.04	-7.74	-8.56	-0.89	-0.92	-0.87	-0.75
	(0.41)	(1.01)	(1.39)	(2.24)	(0.02)	(0.02)	(0.02)	(0.05)
Distance OVERALL	-0.39	-0.66	-2.09	-4.01	-1.37	-1.74	-1.63	-1.23
	(0.03)	(0.04)	(0.09)	(0.16)	(0.09)	(0.09)	(0.06)	(0.06)
Distance INTRA Regional flows	-2.07	-3.45	-8.99	-12.26	-0.90	-0.76	-0.97	-1.03
	(0.18)	(0.33)	(0.65)	(1.14)	(0.12)	(0.14)	(0.10)	(0.12)
Distance EXTRA Regional flows	-0.36	-0.65	-2.03	-3.83	-1.41	-1.81	-1.68	-1.25
	(0.03)	(0.05)	(0.09)	(0.17)	(0.10)	(0.10)	(0.07)	(0.06)

Robust standard errors in parentheses. All estimates are evaluated at the sample mean. The marginal effects for contiguity and barrier dummies are evaluated by measuring the variation of the prediction when the dummy switches from 0 to 1. Relative marginal effects are measured as the ratio between the marginal effect and the relevant baseline prediction. Standard errors are estimated by the Delta method.

APPENDIX

TABLE A1

PRODUCT	Overall share of hospital treatments	description
CS = Complex Surgery	1.7%	Surgical Neurology Pulmonary Surgery Cardiovascular Surgery Transplants
CA = Cancer	7.8%	Surgical Oncology Medical Oncology Chemotherapy and Radiotherapy
BS = Base Surgery	23.6%	Surgical Ophthalmology Surgical Othorinolaryngology Surgical Gastroenterology Orthopedic Surgery Surgical Endocrinology Urologic Surgery Vascular Surgery General Surgery
BM = Base Medicine	47.6%	Medical Neurology Medical Ophthalmology Medical Otorhinolaryngology Pulmonary Medicine Cardiology Medical Gastroenterology Orthopedic Medicine Medical Endocrinology Urologic Medicine Psychiatry Vascular Medicine General Medicine Rehabilitation
EM = Emergency	4.0%	Surgical traumatology Major traumatology Minor traumatology
HIV	0.5%	HIV
DE = Delivery	14.8%	Gynecology Surgical obstetrics Medical obstetrics Neonatology